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How do the recognizability and driving styles of automated vehicles affect human drivers' gap acceptance at T- Intersections?

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ABSTRACT

Future traffic will be composed of both human-driven vehicles (HDVs) and automated vehicles (AVs). To accurately predict the performance of mixed traffic, an important aspect is describing HDV behavior when interacting with AVs. A few exploratory studies show that HDVs change their behavior when interacting with AVs, being influenced by factors such as recognizability and driving style of AVs. Unsignalized priority intersections can significantly affect traffic flow efficiency and safety of the road network. To understand HDV behavior in mixed traffic at unsignalized priority *T*-intersections, a driving simulator experiment was set up in which 95 drivers took part in it. The route in the driving simulator included three *T*-intersections where the drivers had to give priority to traffic on the major road. The participants drove different scenarios which varied in whether the AVs were recognizable or not, and in their driving style (Aggressive or Defensive). The results showed that in mixed traffic having *recognizable aggressive AVs*, drivers accepted significantly larger gaps (and had larger critical gaps) when merging in front of AVs as compared to mixed traffic having either *recognizable defensive AVs* or *recognizable mixed AVs* (composed of both aggressive and defensive). This was not the case when merging in front of an HDV in the same scenarios. Drivers had significantly smaller critical gaps when driving in traffic having non-recognizable aggressive AVs compared to non-recognizable defensive AVs. The findings suggest that human drivers change their gap acceptance behavior in mixed traffic depending on the combined effect of recognizability and driving style of AVs, including accepting shorter gaps in front of *non-recognizable aggressive AVs* and changing their original driving behavior. This could have implications for traffic efficiency and safety at such priority intersections. Decision makers must carefully consider such behavioral adaptations before implementing any policy changes related to AVs and the infrastructure.

1. Introduction

The introduction of Automated Vehicles (AVs) on public roads has been fueled by expected positive impacts on traffic safety, reduction in traffic congestion, and lower environmental impacts (Greenblatt & Shaheen, 2015; Piao et al., 2016). One probable scenario is that AVs are deployed on the existing infrastructure, therefore driving alongside Human Driven Vehicles (HDVs). Such a "mixed" traffic environment consisting of both HDVs and AVs could result in interactions of a different nature. This would especially be noticeable in critical scenarios such as discontinuities (e.g., intersections, weaving sections, on-ramps, and off-ramps) and may

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positively or negatively affect traffic flow operations and safety. Therefore, road authorities and policymakers desire to predict the potential consequences of mixed traffic to take appropriate measures that not only minimize and possibly prevent negative and dangerous effects but also that may drive positive effects. For this, an in-depth understanding of how human drivers might adapt and change their behavior when interacting with AVs compared to when interacting with other HDVs is needed.

Existing studies that aim to predict the traffic flow operations and traffic safety in mixed traffic generally model human driving using models that are developed for 100 % human-driven traffic (Papadoulis et al., 2019; Yao et al., 2020; Ye & Yamamoto, 2018). Recent studies, which are later discussed, including field test experiments, have shown that human drivers adapt their driving behavior in the presence of AVs. Behavioral adaptation is defined as "*any change of driver, traveler, and travel behaviors that occurs following user interaction with a change to the road traffic system, in addition to those behaviors specifically and immediately targeted by the initiators of the change*" (Kulmala & Rama, 2013). While studies have looked at behavioral adaptation in mixed traffic, the focus has primarily been on car-following and lane-changing behavior on straight road sections, while limited attention has been given to discontinuities. A crucial behavior for traffic safety and efficiency at priority *T*-intersections is gap acceptance of a vehicle on a minor road (approach) that wishes to merge onto a major road. Priority intersections are a critical part of the road network that affect the network's traffic efficiency and safety (29 % of road deaths in the Netherlands occurred at intersections (*Road Deaths in the Netherlands.* SWOV Factsheet, 2022). At a priority *T*-intersection, the minor road vehicle generally comes to a complete stop or slows down (before a Stop sign or a Give-Way sign, respectively) and waits until it finds an appropriate gap in the major road traffic stream.

Gap acceptance behavior at priority-controlled intersections in conventional traffic conditions has been extensively studied in the literature. These studies have focused on observing rejected gaps, observing and modeling accepted gaps (Beanland et al., 2013; Yan et al., 2007), estimating critical gaps, and modeling critical gaps (Gattis & Low, 1999; Guo & Lin, 2011; Pollatschek et al., 2002; Rossi et al., 2020). The size of the gaps offered was found to be the most influencing factor in gap acceptance behavior (Beanland et al., 2013). Most existing studies on gap acceptance at priority intersections have looked at conventional traffic conditions. A limited number of studies have investigated the potential behavioral adaptation of human drivers' gap acceptance at unsignalized intersections when interacting with AVs. Trende et al. (2019) used a driving simulator to compare the gap acceptance of drivers at priority intersections in front of HDVs and in front of AVs. Drivers more frequently accepted gaps in front of AVs (drivers were informed that AVs avoided collisions), although all cars drove similarly. Soni et al. (2022) studied gap acceptance behavior in a controlled field test using the Wizard of Oz method. Drivers were found to have significantly smaller critical gaps when merging in front of AVs compared to HDVs, which further reduced when positive information about the AVs was provided. Most other studies focused on investigating drivers' potential behavioral adaptation when interacting with AVs in car-following behavior, and few on lane-changing behavior. Considering the limited studies on gap acceptance, insights from the studies on car-following and lane-changing behavior are summarized below as these can still be useful and relevant for the current study.

Lee et al., (2018) studied human drivers' lane-changing behavior in an AV platoon environment using a driving simulator. They found that human drivers drove more radically as indicated by greater steering magnitude and steering velocity during lane-changing. The duration of lane change preparation tended to increase with increasing AV penetration rate. For example, an increase in AV penetration rate from 0 % to 50 % led to a 60 % increase in lane change preparation duration. Moreover, females and older drivers were less likely to successfully change lanes in general across the different penetration rates. Other studies (Gouy et al., 2014; Zhao et al., 2020; Rahmati et al., 2019; Razmi Rad et al., 2021; Schoenmakers et al., 2021; Fuest et al., 2020; Stange et al., 2022; Zhao et al., 2020) have looked at such behavioral adaptation of human drivers (mainly car-following and lane-changing behaviors) in mixed traffic considering recognizability and driving style of AVs. Gouy et al. (2014) studied the car-following behavior of HDVs when driving next to AV platoons using a driving simulator. They found that drivers adopted smaller average and minimum time headways, and kept a time headway below a threshold of 1 s for a longer duration when driving next to platoons of AVs that maintained time headways of 0.3 s compared to platoons that maintained time headways of 1.4 s. Zhao et al. (2020) conducted a field experiment to study HDVs' car-following behavior when following an AV considering its recognizability. When the AV was recognizable, AV-believers maintained smaller time headways, and AV skeptics maintained larger time headways. When the AV was not recognizable, no difference in behavior was found. Rahmati et al. (2019) also conducted a field experiment to study HDVs' car-following behavior when following a vehicle that drove like an HDV, and also when following a vehicle that drove like an AV (according to a predefined model). When following the AV-like driving vehicle, drivers maintained smoother speed profiles, maintained a smaller gap with the AV, and drove with less abrupt accelerations and decelerations, as compared to when following the HDV-like driving vehicle. Zhong et al. (2019) adopted microsimulation to study the effect of two CACC driving strategies (ad-hoc coordination, and local coordination) on human-driven vehicles, as well as throughput (vehicles per hour) and productivity (ratio of vehicle miles traveled to vehicle hours traveled) of a highway segment. In general, they observed an increase in throughput and productivity with an increasing penetration rate of AVs. The lane change frequency of human-driven vehicles decreased with the increasing penetration rate of AVs. Additionally, the distribution of hard braking observations for human-driven vehicles between the two CACC coordination strategies was significantly different when HDVs followed the AVs but not different when HDVs followed other HDVs.

Razmi Rad et al. (2021) studied HDV car-following and lane-changing behavior in a driving simulator study when driving next to a dedicated lane for AVs and compared that to a mixed traffic situation with no dedicated lanes. The authors found that HDVs adopted shorter time headways with the leader when driving on the lane next to the dedicated lane (i.e., the middle lane) and accepted shorter gaps when lane-changing. Moreover, younger male drivers kept smaller headways compared to older female drivers. Schoenmakers et al. (2021) also studied the car-following behavior of HDVs when driving next to a dedicated lane for AVs and found that drivers maintained significantly lower headways when driving next to AV platoons driving on dedicated lanes. Fuest et al. (2020), using a driving simulator, studied the differences in perception of AVs and actual driving behavior of drivers around AVs in roadworks, traffic jams, and lane change situations, considering AV recognizability. They found that the recognizability of AVs did not affect the way they are perceived by human drivers in all situations. However, most drivers stated that they preferred that AVs would be marked (i.e., recognizable). Additionally, drivers did not change their lane change behavior (measured by the number of lane changes and time until lane change) and their car-following behavior (measured by time headway) when the AVs were recognizable versus when they were not recognizable. Stange et al. (2022) performed a driving simulator experiment to study the subjective experience and driving behavior of human drivers in mixed traffic with different appearances (using eHMIs) and penetration rate of AVs. They found that drivers experienced mixed traffic with higher AV penetration levels as less comfortable and less efficient, but not as dangerous as conventional traffic and lower AV penetration levels scenarios. Appearance differences through eHMIs did not affect driver behavior. However, drivers' average speed decreased when the AV penetration rate was 25 % and higher, and the percentage of safety–critical interactions with their lead vehicle increased with increasing AV penetration rate.

Useful insights into human-AV interactions can also be derived from studies looking at vulnerable road users. Hagenzieker et al. (2020) conducted a photo experiment to study the expectations and behavioral intentions of cyclists when interacting with AVs (two types of appearances) as compared to manually driven vehicles. They found that participants were less confident to be noticed when interacting with both AV types as compared to the manually driven vehicle, and looked significantly longer at the AVs during their first interactions. In the second interaction, participants were more confident that the AVs would stop for them. Zhao et al. (2022) studied pedestrians' intention to cross the road in front of AVs in risky situations using a questionnaire. They found that pedestrians had significantly higher intentions to cross in front of AVs as compared to HDVs. They also reported lower risk perception and greater trust in this type of vehicle.

From the studies discussed above, it emerges that human drivers tend to change their behavior when AVs are in their surroundings in traffic (Trende et al., 2019; Soni et al., 2020; Lee et al., 2018; Gouy et al., 2014; Zhao et al., 2020; Rahmati et al., 2019; Razmi Rad et al., 2021; Schoenmakers et al., 2021; Fuest et al., 2020; Stange et al., 2022). Factors such as the AV appearance (recognizable and not recognizable), its driving style (most studies assume AVs to have shorter time headways and smoother driving profiles), personal characteristics of human drivers such as age and gender seem to affect the observed behavioral adaptation. With the increasing deployment of AVs in traffic, knowledge of such interactions at priority intersections is required, especially crucial aspects of AVs such as their recognizability and driving style. Understanding potential changes in human driving behavior in mixed AV-HDV traffic is crucial as policymakers and car manufacturers use the results of such simulation studies to take (proactive) critical decisions. In this paper, the notion of *behavioral adaptation* is used to describe any change in gap acceptance behavior of drivers in mixed traffic due to aspects such as recognizability and the driving style of AVs. An example of such behavioral adaptation could be that drivers accept significantly smaller gaps when they merge in front of an AV as compared to the gaps they accepted in HDV-only traffic.

2. Scope and research questions

This paper focuses on studying the gap acceptance behavior of human drivers in mixed traffic at priority *T*-intersections using a driving simulator. Following the identification of the research gaps, the main research question is defined as follows:

How do human drivers perform gap acceptance maneuvers in mixed (automated and human-driven) traffic at priority T-intersections?

To answer the main research question, the following sub-research questions were defined (considering priority *T*-intersections in mixed traffic):

1. Does the recognizability of AVs by itself affect human drivers' accepted gaps?
2. Does the driving style of AVs by itself affect human drivers' accepted gaps?
3. How does the recognizability and driving style of AVs, together, affect human drivers' accepted gaps?

Fig. 1. A participant using the driving simulator during the experiment.

4. How do the above factors affect human drivers' critical gaps at priority *T*-intersections in mixed traffic?

This research makes certain assumptions to answer the research questions. Firstly, the penetration rate of AVs is fixed at 50 % to characterize a balanced HDV-AV traffic mix. Secondly, the driving behavioral differences between AVs and HDVs are defined by their desired speeds and their following time gaps. The next section explains the research methodology and elaborates on these design parameters.

3. Research methodology

A driving simulator experiment was designed to answer the formulated research questions. This section describes the set-up of the experiment, the experimental design, and the data collection and data processing.

3.1. Experiment set-up & participants' recruitment

A virtual reality experiment was set up using the driving simulator located at the Transport & Planning department, Delft University of Technology, the Netherlands. The software SCANeR (v1.9) by AV Simulation was used to design the scenarios in the driving simulator. The driving simulator, as shown in Fig. 1, is a fixed base driving simulator comprised of a dashboard mock-up with three 4 K high-resolution screens, providing approximately a 180° vision, with a Fanatec steering wheel and pedals.

The experiment also included a pre-experiment and a post-experiment questionnaire. The pre-experiment questionnaire collected information on the participants' demographics. The post-experiment questionnaire collected information on whether the participant experienced motion sickness (Kennedy et al., 1993) and their experienced presence in the simulator (Witmer & Singer, 1998) during the experiment. The experiment was approved by the Human Resource and Ethics Committee (HREC) of the Delft University of Technology.

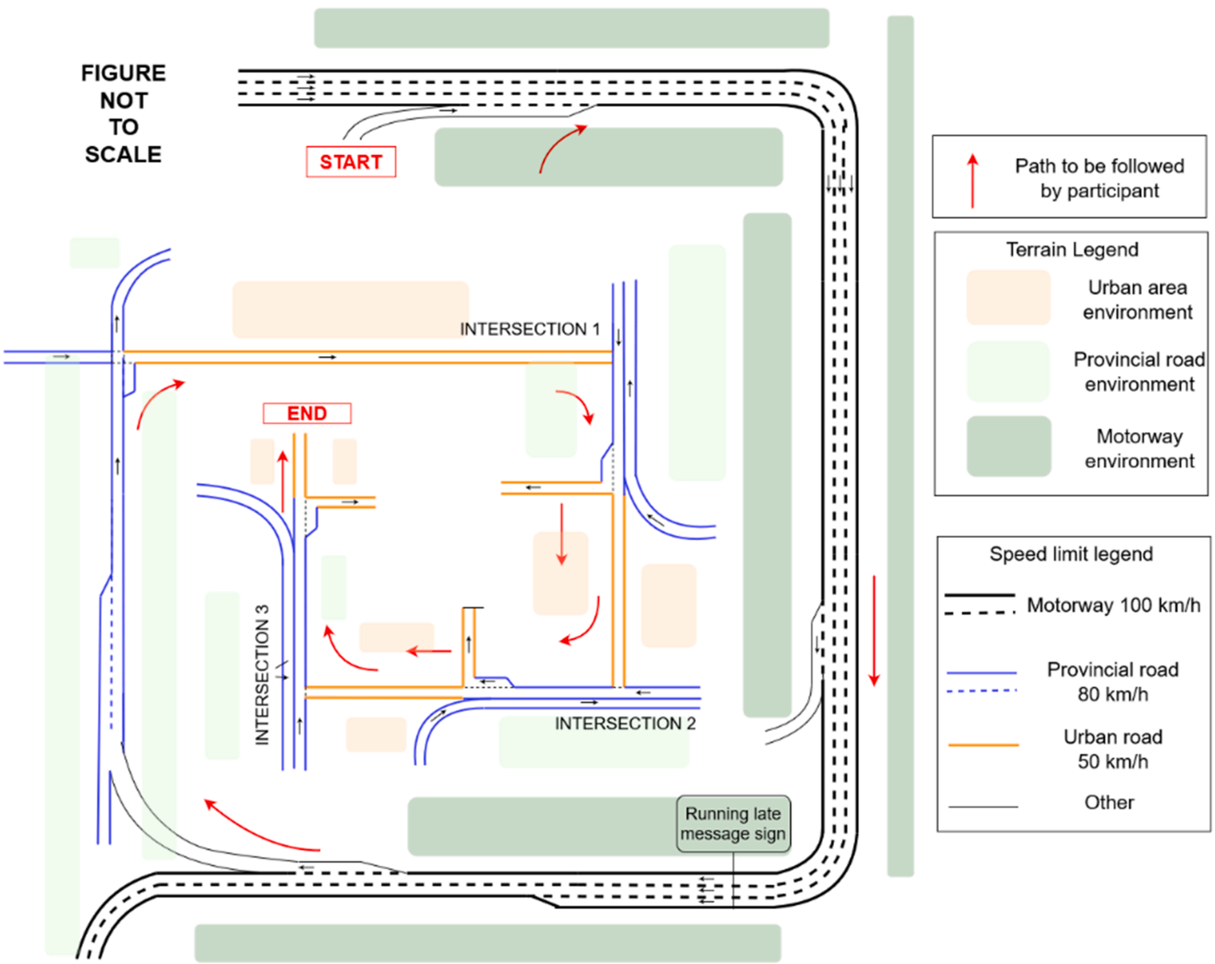


Fig. 2. Depiction of the route driven by the participants in the experiment.

Participants for the experiment were recruited through advertisements in social media and newspapers. Anyone with a valid driving license could participate. The experiment per participant lasted between 60 and 90 min, including a briefing, familiarization drive, the experiment scenarios with sufficient breaks, and post-experiment questionnaires. The participants were compensated with a voucher of 15€ each. A total of 114 drivers participated in the experiment.

3.2. Route

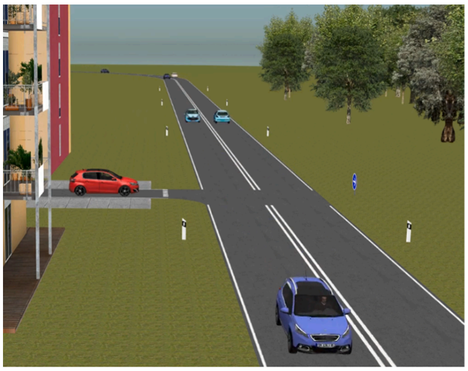
The route was designed to allow drivers to sufficiently experience the traffic conditions before approaching the intersections. It consisted of several motorway sections, provincial (regional) road sections, and three priority *T*-intersections. Each *T*-intersection consisted of an urban road (the minor road) intersecting with a provincial road (the major road). The defined speed limit was 100 km/h on the motorway, 80 km/h on the provincial roads, and 50 km/h on urban roads. These were defined as per the current Dutch road system. Fig. 2 depicts a sketch of the route designed in the driving simulator. This paper focuses on analyzing the behavior of the participants at the three priority *T*-intersections. A stop sign placed before each intersection ensured that drivers came to a full stop before navigating the intersection. These intersections are positioned towards the end of the route. This allowed the participants to drive and experience different traffic conditions in the respective scenarios before reaching the intersections. Fig. 3 (a, b) shows an example situation at a *T*-intersection in the driving simulator environment.

3.3. Experiment design

Two variables primarily varied in the experiment: the driving style of AVs, and their recognizability. The participants were assigned randomly to one of three groups: Defensive AVs, Aggressive AVs, and Mixed AVs. The group determined the driving style of AVs that a participant encountered in the experiment. For example, participants in the defensive AVs group only encountered defensive AVs. In the scenario of mixed AVs, both defensive and aggressive AVs were present in the volume ratio of 3:2. Throughout the experiment the penetration level of AVs was fixed at 50 %. Table 1 shows the differences in the driving behaviors between HDVs and AVs in the experiment. The desired car-following time gap parameters of AVs were fixed based on a range of commercial ACC systems that were openly available (Makridis et al., 2021; Raju et al., 2022). The headway for HDVs were based on (Taieb-Maimon & Shinar, 2016; Winkelbauer et al., 2019). The desired speed of both Defensive and Aggressive AVs was set to speed limit as we expect that AVs would not be explicitly designed to exceed a legal speed limit.

The experiment design aimed to separately observe the effects of AVs' recognizability and their driving style on human driving behavior as well as their combined effects. Each participant drove four scenarios, excluding a familiarization drive. The scenarios differed in two aspects: the recognizability and the driving style of AVs. Table 2 provides an overview of the four scenarios. Fig. 4 provides an overview of the groups and the scenarios.

At the three *T*-intersections, traffic on the major road was generated with gaps drawn randomly between 3 and 10 s from a uniform distribution to ensure that the offered gaps were not too small nor too large (Beanland et al., 2013). Therefore, the distinction between Aggressive and Defensive AVs did not apply to traffic on the major road at the *T*-intersections. As the participants drive on the motorway and the provincial road before approaching the *T*-intersections, their resulting decisions of gap acceptance are expected to be influenced by the kind of traffic they interacted with in that scenario, i.e., by a "carry-over" effect. In scenarios 1 and 2, all vehicles appeared as HDVs, including the vehicles on the major roads at the *T*-intersections. In Scenarios 3 and 4, 50 % of the traffic appeared as AVs. The vehicles on the major roads at the *T*-intersections can therefore appear as AVs or as HDVs in these scenarios. Fig. 5 shows the appearance of AVs (a) and HDVs (b) in the driving simulator. Participants were informed of the appearance of AVs in the experiment and were able to differentiate AVs from the other traffic. The participants did not receive any explicit information regarding the driving



(a)

(b)

Fig. 3. Situation at a *T*-intersection in the simulator (a) Driver in the red car waiting to turn right onto the major road) (b) a picture from the actual simulator where the driver is waiting to turn right. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Driving Behavior Parameters of AVs and HDVs in the Experiment.

Vehicle	Desired speed	Desired car-following time gap (s)
HDVs	Between 90 % and 110 % of the speed limit, drawn randomly (uniform distribution)	Minimum 0.5; Maximum 1.5; Truncated negative exponential distribution
Defensive AVs	Set to speed limit	3.5
Aggressive AVs	Set to speed limit	1.5
Mixed AVs	This group had both Defensive and Aggressive AVs in a volume ratio of 3:2	

Table 2
Scenarios and their Definition.

Scenario number	Description	Recognizability of AVs	Driving style of AVs	Nomenclature/code
S1	Only HDVs	–	–	App (HDV) DS (HDV)
S2	HDVs & NR–AVs DS-AV	Not recognizable (NR)	AV	App (HDV) DS (AV)
S3	HDVs & R-AVs DS- AV	Recognizable (R)	AV	App (AV) DS (AV)
S4	HDVs & R-AVs DS- HDV	Recognizable (R)	HDV	App (AV) DS (HDV)

*App – Appearance; DS – Driving style.

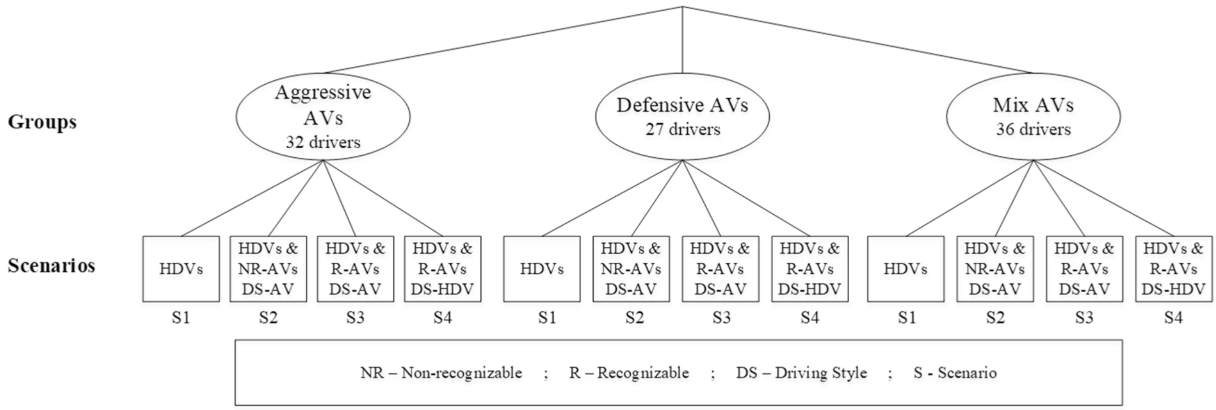


Fig. 4. Overview of the division of drivers over the three groups and depiction of the four scenarios (S1-S4).

(a) Appearance of Automated Vehicles **(b)** Appearance of Human-Driven Vehicles

Fig. 5. Appearance of vehicles in the driving simulator environment.

style of the AVs that they will encounter. AVs in the aggressive, defensive, and mixed groups had the same appearance when they were recognizable. Each scenario lasted, on average, between 10 and 12 min. There were sufficient breaks provided in between scenarios. Additionally, to counter the learning effect, the participants experienced the scenarios in random order.

3.4. Experiment procedure

Before the start of the experiment, drivers signed a consent form and completed the pre-questionnaire. Then, they drove a familiarization drive to get acquainted with the driving simulator environment and the vehicle controls. After every scenario, drivers were asked to take a break. At the end of the experiment, drivers filled in the post-experiment questionnaire. In the experiment, the participating drivers were instructed to drive as they normally do on a work commute assuming they had to attend a meeting when they get there, to induce a sense of time pressure as can be expected on everyday commutes. Additionally, a message sign was displayed in the middle of the scenario towards the end of the motorway section (as displayed in Fig. 2) stating that they were a few minutes late, to prevent drivers from being “too relaxed” in the simulator.

4. Data collection, data processing & analysis method

The collected data in the driving simulator contained the timestamp along with variables such as speed, acceleration, and position for every vehicle in the scenario. These raw data, which were collected at a frequency of 20 Hz, was later reduced to 4 Hz to decrease the processing time while still maintaining 4 data points per second. These reduced data were then processed using Python code to appropriately identify moments in time and relevant indicators for studying gap acceptance behavior. The resulting indicators from the simulator data were then matched to the appropriate questionnaire responses by the participants. The analysis was divided into two parts: accepted gap analysis, and critical gap analysis.

T-intersections are generally characterized by two conflicting roads, a major road, and a minor road, according to the magnitude of their traffic volumes. When a sufficient gap arises on the major road, drivers on the minor road accept the gap by merging onto the major road. The vehicle on the major road that the minor road driver merges in front of is termed the “follower”, and the vehicle in front of the driver after accepting the gap is termed the “leader”. The gap that is accepted is termed as “accepted gap”, defined as the time gap (in seconds) between the front of the follower and the rear of the leader. The gaps that the drivers do not accept are termed “rejected gaps”. Drivers are also presumed to have a critical gap which is the minimum gap they are willing to accept. The critical gap is a hard threshold below which the driver always rejects the gap. Accepted gaps and rejected gaps can be observed, but the critical gap can only be estimated. In this research, the accepted gap analysis consisted of statistical testing and modeling. Wherever relevant, analyses were separated according to within groups/scenarios and between groups/scenarios. Appropriate statistical tests were used, such as the Friedman’s Test (comparing means of multiple scenarios within subjects), the Wilcoxon Signed Ranks Test (post hoc analysis after Friedman’s Test), the Kruskal-Wallis Test (comparing means of groups between subjects), the Mann-Whitney Test (Post hoc analysis after Kruskal Wallis Test), and the Levene’s Test (comparing variance between subjects). For modeling, a generalized linear model was adopted. The critical gap estimation was performed using Wu’s method (Wu, 2006), which is based on the probability equilibrium between the rejected and the accepted gaps. It provides a true average of the critical headway and was found to give similar results of the mean critical gap as compared to the Maximum Likelihood, and without requiring any major assumptions on the consistency and homogeneity of drivers (Amin & Maurya, 2015). However, to use the method, the minimum accepted gap must be smaller than the maximum rejected gap. Statistical testing of the estimated critical gaps was performed using the Kolmogorov–Smirnov test. The significance level was kept at 0.05.

While presenting the results, specific nomenclature is used. The four scenarios differ in the appearance (*App*) of the AVs and their driving styles (*DS*). As an example, *App (AV) DS (HDV)* describes the scenario where AVs appear as AVs (that is, they are recognizable) and drive the same as HDVs. At the intersections, it is also interesting to study the type of vehicle the participant merged in front of, that is, the immediate following vehicle after the participant accepts a gap. The appearance of this vehicle could be AV or HDV. The results also present an analysis of gap acceptance for different types of followers within the same scenario. For instance, *App (AV) DS (AV) Follower App (HDV)* describes the gap acceptance observations for the scenario where AVs were recognizable, driving according to the AV driving style, but the participant accepted a gap at the intersection in front of an HDV. As there are three groups, namely Aggressive (*Agg*), Defensive (*Def*), and Mixed (*Mix*) AVs, this may also be specified in the nomenclature as *DS (Agg AV), DS (Def AV),* or *DS (Mix AV),* respectively.

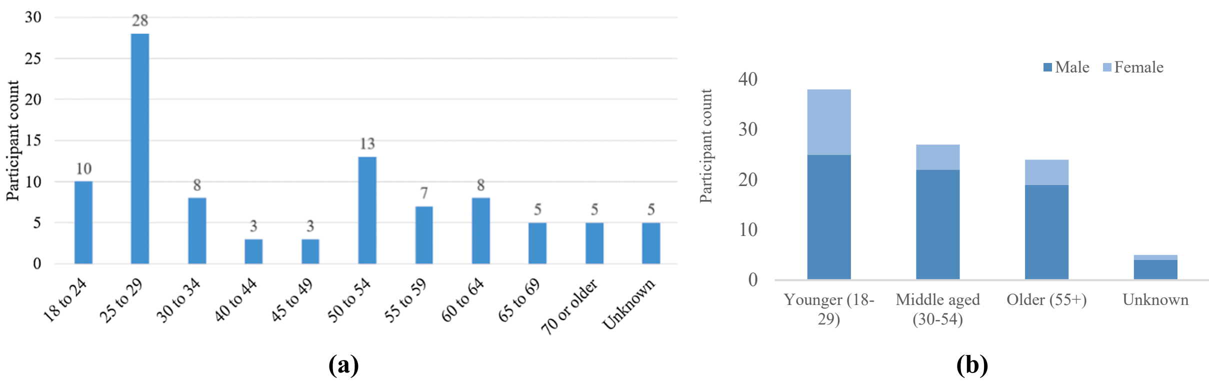


Fig. 6. (a) Age group distribution (95 participants) (b) Participants split between age categories and gender.

5. Results

The results are structured as follows. First, the gender and age distributions of the participants are shown. Next, descriptive statistics of accepted gaps at the three intersections, for the different scenarios and groups are presented. Then, the analyses and results for each sub-research question are presented separately.

5.1. Participants

Of the 114 participants who participated, 12 (10.5 %) experienced severe nausea and/or were unable to complete the experiment, and therefore were excluded from the analysis. Moreover, 7 participants were also excluded due to erroneous behavior at the intersections (not following instructions), or for very poor driving behavior (abnormal driving). This resulted in a final gap acceptance dataset of 95 participants of which 71 (74.7 %) were male and 24 females. Fig. 6 (a) shows the distribution of the participants by age group. The age groups were combined into three age categories: Younger (18–29), Middle-aged (30–54), and Older (55 +) to ensure a reasonable number in each category. It was also attempted to have both gender groups in each of these age categories (Fig. 6(b)).

5.2. Descriptive statistics of accepted gaps

Table 3 shows the number of accepted gap and rejected gap observations recorded for different conditions in the experiment. The total number of accepted gap observations in the dataset was 948 (excluding the familiarization drive).

In this study, gap acceptance behavior was measured by the total accepted gap (in seconds), henceforth referred to as just the “accepted gap”. Accepted gap is defined by the sum of the lag (with follower) and the lead (with leader) time gap at the instant the subject vehicle entered the major road. This was calculated using the speed and distance to the intersection of the leader and follower vehicles at the instant the subject vehicle entered the major road. The speeds of the vehicles on the major road were constant until the subject vehicle merged into the major road. For statistical analysis, the three accepted gap observations at the three intersections for every scenario (for every participant) were averaged. The mean accepted gaps at the three intersections ranged between 7.13 s and 7.31 s with the standard deviation ranging between 1.44 s and 1.55 s. Friedman’s test showed that there was no statistically significant difference in the accepted gaps between the three intersections $\chi 2(3) = 2.831$, $p = 0.243$. Therefore, no significant information was lost by averaging the observations at the three intersections. However, for modeling, observations at all three intersections were considered.

5.3. Does the AV recognizability by itself affect drivers’ accepted gaps?

For statistically testing the effect of AV recognizability by itself, first, the accepted gaps of scenarios App (AV) DS (AV) and App (HDV) DS (AV) were compared for each of the three groups, that is, aggressive, defensive, and mixed. Table 4 presents the median and standard deviation of the accepted gaps for the two scenarios for the three groups as well as the Wilcoxon signed rank test results.

There were no significant differences found in the accepted gaps between the two scenarios for the defensive, aggressive, and mixed groups. This suggested that irrespective of the driving style of AVs, their recognizability did not significantly affect drivers’ accepted gaps. The difference for the aggressive group, however, was close to being significant (at the 95 % confidence level). The same was tested for different age and gender categories. There were no significant differences for any of the categories.

The two scenarios App (AV) DS (HDV) and App (HDV) DS (HDV) were also compared for each of the three groups. The results are presented in Table 4. There were no significant differences found in the accepted gaps for these two scenarios for the defensive, the aggressive, and the mixed groups. This suggests that when AVs have the same driving style as HDVs, their appearance by itself did not have a significant effect on human drivers’ accepted gaps.

5.4. Does the AV driving style by itself affect drivers’ accepted gaps?

For statistically testing the effect of AV driving style by itself, the accepted gaps of the defensive, aggressive, and mixed groups were

Table 3
The number of Gap Acceptance Observations in the Dataset.

Condition	Number of accepted gap observations	Number of rejected gap observations	% Accepted gaps
Complete dataset	948	2092	31 %
App (HDV) DS (HDV)	242	524	32 %
App (HDV) DS (AV)	240	501	32 %
App (AV) DS (AV)	241	569	30 %
App (AV) DS (HDV)	225	498	31 %
Def	269	608	31 %
Agg	318	760	29 %
Mix	361	724	33 %
Follower App (HDV)	709	1537	32 %
Follower App (AV)	239	555	30 %

Table 4
Accepted gaps for scenarios App (AV) DS (AV) and App (HDV) DS (AV) within the three groups.

Group	Median (and standard deviation) of accepted gap		
	App (AV) DS (AV)	App (HDV) DS (AV)	Wilcoxon signed rank test
Defensive AV Group	7.43 (0.79)	6.89 (0.82)	Z = -0.179, p = 0.858
Aggressive AV Group	7.97 (0.93)	6.98 (0.89)	Z = -1.825, p = 0.068
Mixed AV Group	7.32 (0.97)	7.28 (1.18)	Z = -0.168, p = 0.866
	App (AV) DS (HDV)	**App (HDV) DS (HDV)**	
Defensive AV Group	6.89 (0.82)	7.22 (0.96)	Z = -0.155, p = 0.877
Aggressive AV Group	6.98 (0.89)	7.82 (1.19)	Z = -0.958, p = 0.338
Mixed AV Group	7.28 (1.18)	7.33 (1.06)	Z = -0.308, p = 0.758

compared for the scenarios App (AV) DS (AV) and App (HDV) DS (AV). The Kruskal Wallis test was used to test the differences between the three groups for the two scenarios. Table 5 presents these results. Both scenarios App (AV) DS (AV) and App (HDV) DS (AV) were not significantly different between the three groups. This suggests that the AV driving style by itself did not affect drivers' accepted gaps, for both recognizable and unrecognizable AVs.

The same was tested for the different age and gender categories for the two scenarios. No significant differences were observed between the three groups for any of the age and gender categories.

5.5. How do the recognizability and driving style of AVs, together, affect drivers' accepted gaps?

Fig. 7 presents the box plot of accepted gaps for scenario-group combinations. In Fig. 7, driving styles are color coded so that the groups with aggressive AVs are in a range of red, those with defensive AVs are in a range of green, and those with mixed AVs are in a range of blue. HDVs are color-coded in a range of grey. The lighter and darker shades indicate whether the AVs are non-recognizable or recognizable, respectively. It is observed that drivers accepted larger gaps when interacting with a vehicle that appeared as an AV and had an aggressive driving style (*App (AV) DS (Agg AV)*).

A generalized linear model was estimated to understand the effects of recognizability and driving style on the accepted gaps. For this, accepted gap observations from scenarios *App (AV) DS (AV)* and App *(HDV) DS (AV)* were used. Table 6 presents the estimated model. The reference condition is *App (AV) Follower App (AV) DS (Agg AV)*. The model contains three types of terms: first, the combination of appearance (App) and follower appearance (*Follower App*), second, the AV driving style (*DS*), and third, the interaction between these two terms. Drivers accepted smaller gaps when driving in the conditions *App (AV) Follower App (HDV)* and *App (HDV) Follower App (HDV)* compared to the gaps they accept in the *App (AV) Follower App (AV)* condition. Drivers also tended to accept smaller gaps in the condition *DS (Def AV)* and *DS (Mix AV)* compared to the *DS (Agg AV)* condition. Considering the interaction terms, the condition *App (AV) Follower App (AV)* with *DS (Agg AV)* resulted in the largest accepted gaps compared to any other condition.

In Fig. 8, the respective scenario-group (indicated by *App* and *DS*) and follower appearance (indicated by *Follower App*) for each boxplot is indicated by a tabular × axis label. It can be observed that the median accepted gap for the case *App (AV) DS (Agg AV) Follower App (AV)* was the highest.

5.6. How do the above factors affect human drivers' critical gaps at priority T-intersections in mixed traffic?

Wu's method was used to estimate the critical gaps for different conditions. Wu's method provides cumulative distribution functions for the critical gaps. Fig. 9 presents an example of the cumulative density functions of rejected, critical, and accepted gaps for the App (AV) DS (AV) condition. Fig. 10 presents the cumulative density functions of critical gaps for different conditions.

The mean and standard deviation of the distributions can also be computed. Table 7 presents the calculated mean and standard deviations of the critical gaps for different conditions. As can be noticed the mean critical gap for the scenario App (AV) DS (Def AV) Follower App (AV) was the lowest, while for App (AV) DS (Agg AV) Follower App (AV) was the highest. The 2-sample Kolmogorov–Smirnov test was used to test differences between the distributions of critical gaps of different conditions. As the KS test assumes independent samples, groups of conditions, described in Table 7, that could be compared were (5, 6, 7), (8, 9, 10), (11, 12, 13), (14, 15, 16), (17, 18), and (19, 20, 21).

The 2-sample K-S test was used to check significant differences. As Wu's method yields the cumulative density function values the 2-sample KS test was manually performed in Python. Using linear interpolation, the CDF values for the same gap sizes were computed and their difference was measured between two conditions. Table 8 presents the results with the largest difference (D-statistic) and the

Table 5
Accepted gaps for scenarios App (AV) DS (AV) and App (HDV) DS (AV) between the three groups.

Scenario	Median (and standard deviation) of accepted gap			
	Defensive group	Aggressive group	Mixed group	Kruskal-Wallis test
App (AV) DS (AV)	7.43 (0.79)	7.97 (0.93)	7.32 (0.97)	H (2) = 2.965, p = 0.227
App (HDV) DS (AV)	6.89 (0.82)	6.98 (0.89)	7.28 (1.18)	H(2) = 1.528, p = 0.466

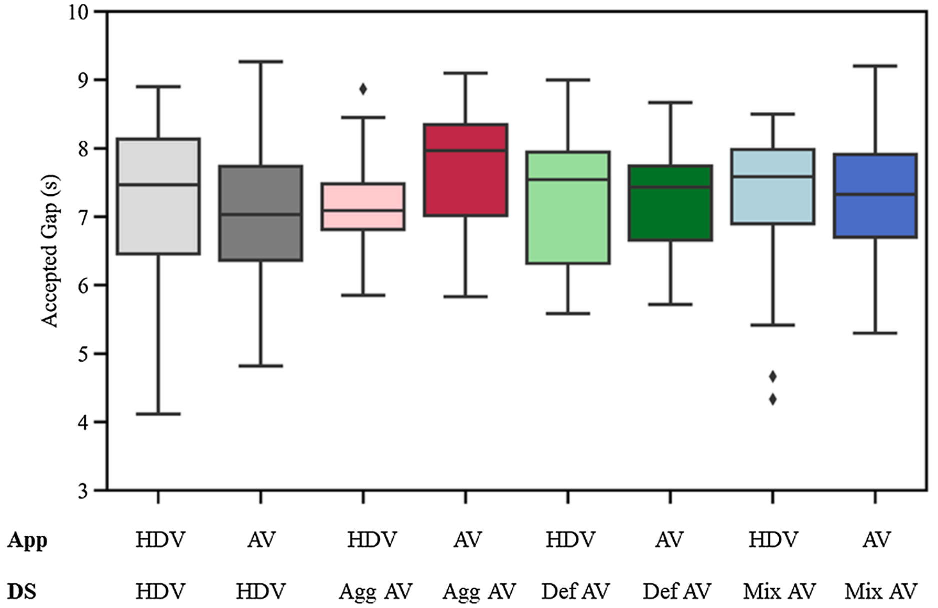


Fig. 7. Accepted gap for different scenario-groups (boxplots illustrate the distribution of the data represented by the "minimum", first quartile (Q1), median, third quartile (Q3), and the "maximum". The dots (outside the whiskers) indicate outliers in the observations.).

Table 6
Generalised linear model results for accepted gap for scenarios App (AV) DS (AV) and App (HDV) DS (AV).

Coefficients	Estimate	Std. error	t value	Pr (>|t|)
(Intercept)	*7.918*	*0.236*	*33.556*	*< 2e-16 ****
App (AV) Follower App (HDV)	*−0.738*	*0.355*	*−2.079*	*0.038 **
App (HDV) Follower App (HDV)	*−0.817*	*0.293*	*−2.790*	*0.005 ***
DS (Def)	*−0.862*	*0.374*	*−2.302*	*0.021 **
DS (Mix)	*−1.004*	*0.315*	*−3.181*	*0.001 ***
App (AV) Follower App (HDV) DS (Def AV)	*1.022*	*0.516*	*1.980*	*0.048 **
App (HDV) Follower App (HDV) DS (Def AV)	*0.975*	*0.452*	*2.156*	*0.031 **
App (AV) Follower App (HDV) DS (Mix AV)	*1.403*	*0.466*	*3.011*	*0.002 ***
App (HDV) Follower App (HDV) DS (Mix AV)	*1.157*	*0.390*	*2.963*	*0.003 ***
AIC: 1621.6				

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '' 1.

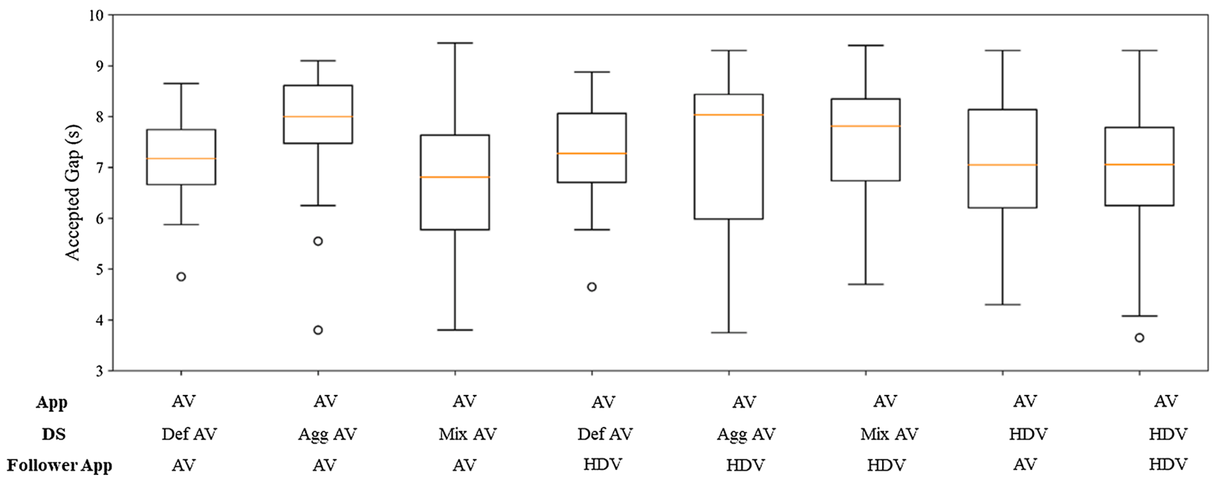


Fig. 8. Accepted gap for different scenario-group-follower appearance combinations.

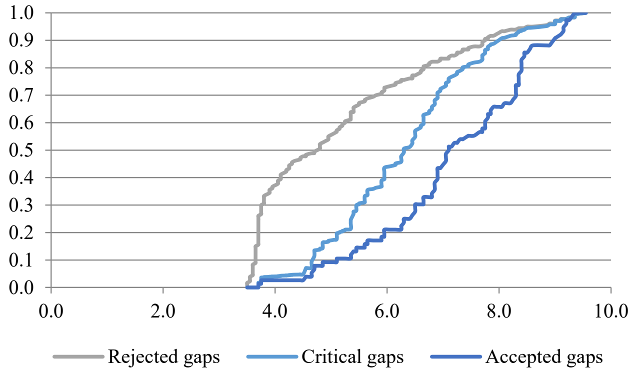


Fig. 9. CDF of rejected, critical, and accepted gaps for the App (AV) DS (AV) condition.

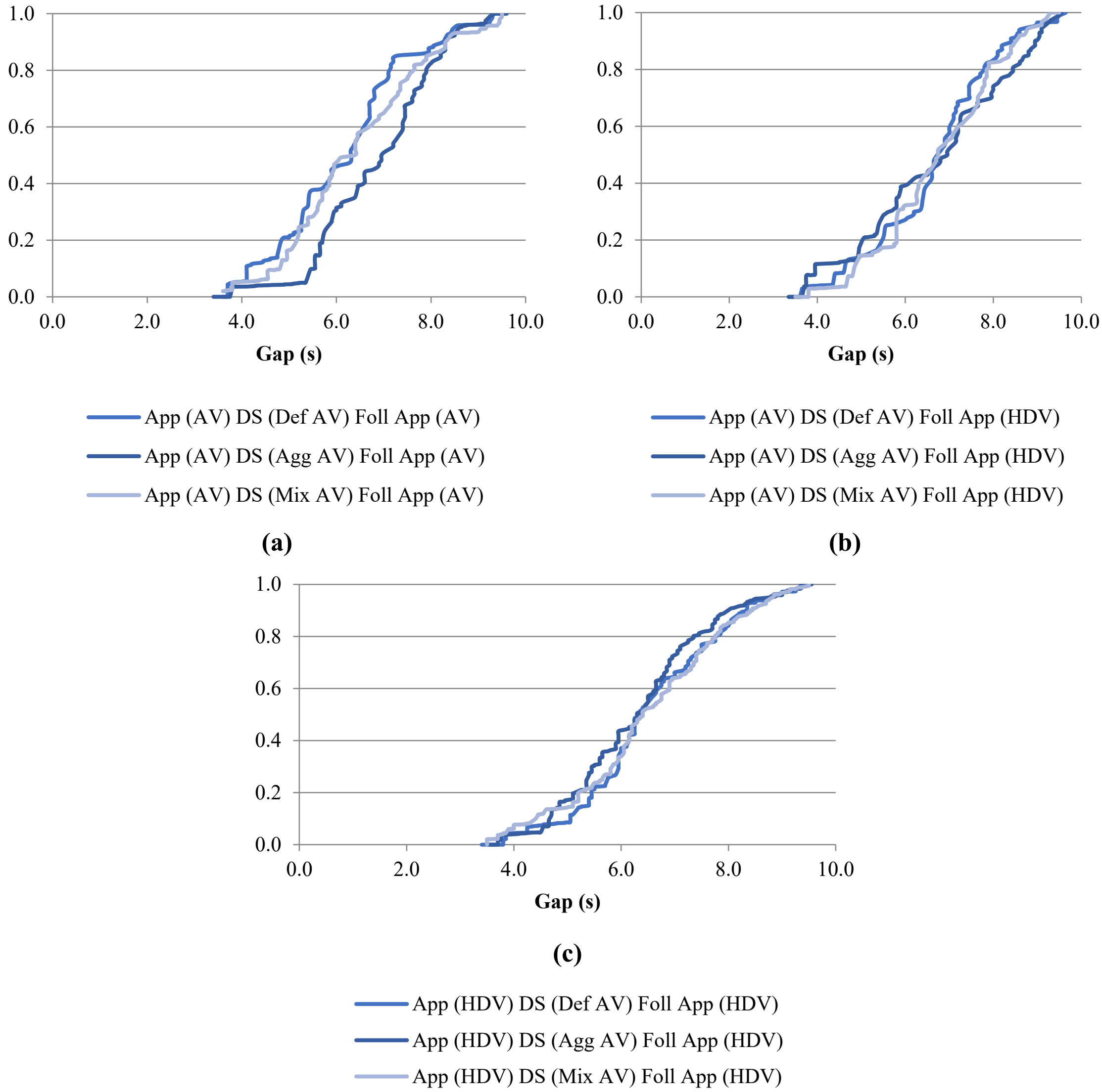


Fig. 10. CDF of critical gaps for different groups (recognizable AVs) when merging in front of (a) an AV follower, (b) an HDV follower, and (c) when in traffic with non-recognizable AVs.

Table 7
Critical gap mean and standard deviation for different conditions.

Condition no.	Description	Critical gap (s)	
		Mean	SD
Scenarios			
1	App (HDV) DS (HDV)	6.43	1.43
2	App (HDV) DS (AV)	6.44	1.36
3	App (AV) DS (AV)	6.59	1.42
4	App (AV) DS (HDV)	6.33	1.52
Groups			
5	Def	6.43	1.42
6	Agg	6.41	1.42
7	Mix	6.51	1.46
Scenario-Group-Follower App			
8	App (AV) DS (Def AV) Follower App (AV)	**6.15**	1.38
9	App (AV) DS (Agg AV) Follower App (AV)	**6.86**	1.22
10	App (AV) DS (Mix AV) Follower App (AV)	6.32	1.64
11	App (AV) DS (Def AV) Follower App (HDV)	6.66	1.37
12	App (AV) DS (Agg AV) Follower App (HDV)	6.69	1.69
13	App (AV) DS (Mix AV) Follower App (HDV)	6.76	1.34
14	App (HDV) DS (Def AV) Follower App (HDV)	6.53	1.30
15	App (HDV) DS (Agg AV) Follower App (HDV)	6.31	1.30
16	App (HDV) DS (Mix AV) Follower App (HDV)	6.48	1.43
Gender and age			
17	Female drivers	6.50	1.46
18	Male drivers	6.44	1.41
19	Younger drivers	6.40	1.47
20	Middle-aged drivers	6.49	1.41
21	Older drivers	6.43	1.33

critical D values for the conducted tests. Firstly, there was **no significant difference** between the different groups (i.e., conditions 5, 6, and 7). This indicated that at an aggregate level over all the scenarios, critical gaps of drivers in the defensive, aggressive, and mixed group were not significantly different. Secondly, when merging in front of a recognizable AV, the critical gap of drivers driving in the recognizable and aggressive AV traffic environment (i.e., condition 9) was **significantly larger** than that of drivers driving in the defensive and mixed traffic environment (i.e., conditions 8 and 10). A **significant difference** in critical gaps was also found between defensive (i.e., condition 14) and aggressive (i.e., condition 15) AV traffic when AVs were not recognizable. Interestingly here, the critical gaps in the aggressive condition were smaller than in the defensive condition. This suggests that drivers tended to follow headways of the surrounding traffic when aggressive AVs were not recognizable. There was **no significant difference** between conditions 11, 12, 13 and between conditions 14, 16 and 15,16. This indicates that when merging in front of an HDV, there was no difference in the critical gap of drivers when driving in Defensive, Aggressive, or Mixed recognizable AV traffic. There was also **no significant difference** in the critical gap of drivers between Defensive and Mixed non-recognizable AV traffic. Testing between gender and age groups revealed **no significant difference** between Female and Male drivers and **no significant difference** between Younger, Middle-aged, and Older drivers. This indicates that gender and age did not affect critical gaps.

Table 8
Critical gap mean and standard deviation for different conditions.

Condition 1	Condition 2	D-stat	Critical D	Inference on distributions
Def	Agg	0.041	0.070	Similar
Def	Mix	0.046	0.070	Similar
Agg	Mix	0.056	0.067	Similar
App (AV) DS (Def AV) Follower App (AV)	**App (AV) DS (Agg AV) Follower App (AV)**	**0.300**	**0.169**	**Different**
App (AV) DS (Def AV) Follower App (AV)	App (AV) DS (Mix AV) Follower App (AV)	0.144	0.176	Similar
App (AV) DS (Agg AV) Follower App (AV)	**App (AV) DS (Mix AV) Follower App (AV)**	**0.205**	**0.158**	**Different**
App (AV) DS (Def AV) Follower App (HDV)	App (AV) DS (Agg AV) Follower App (HDV)	0.128	0.181	Similar
App (AV) DS (Def AV) Follower App (HDV)	App (AV) DS (Mix AV) Follower App (HDV)	0.113	0.166	Similar
App (AV) DS (Agg AV) Follower App (HDV)	App (AV) DS (Mix AV) Follower App (HDV)	0.131	0.176	Similar
App (HDV) DS (Def AV) Follower App (HDV)	**App (HDV) DS (Agg AV) Follower App (HDV)**	**0.131**	**0.130**	**Different**
App (HDV) DS (Def AV) Follower App (HDV)	App (HDV) DS (Mix AV) Follower App (HDV)	0.065	0.129	Similar
App (HDV) DS (Agg AV) Follower App (HDV)	App (HDV) DS (Mix AV) Follower App (HDV)	0.118	0.123	Similar
Female	Male	0.034	0.064	Similar
Younger	Middle-aged	0.057	0.066	Similar
Younger	Older	0.057	0.074	Similar
Middle-aged	Older	0.054	0.080	Similar

6. Discussion & conclusions

A driving simulator experiment was designed to study whether and how the recognizability and the driving style of AVs affect (HDV) drivers' accepted gaps and critical gaps at priority *T*-intersections. This section first summarizes the key findings as answers to the research questions and then reflects on these findings with respect to findings from previous studies. The study's limitations are also discussed.

6.1. Summary of findings

Testing **the effect of recognizability of AVs** (research question 1) revealed that recognizability by itself did not have any effect on the accepted gaps. This is the case as well for each of the three groups (aggressive AVs, defensive AVs, mixed AVs), indicating that for all of the three groups recognizability by itself did not affect drivers' accepted gaps, irrespective of whether the AVs drove like HDVs or according to their respective AV driving style. However, drivers were observed to have close to significantly larger gaps when aggressive AVs were recognizable compared to when they were not recognizable. No effects of recognizability were found also for any age and gender category.

Testing **the effect of driving style of AVs** (research question 2) revealed that the driving style by itself did not have any effect on drivers' accepted gaps. No significant differences in accepted gaps were observed between aggressive, defensive, and mixed AV driving styles. This was the case for both when the AVs were recognizable and when they were not recognizable. No significant effects of AV driving style were found for the age and gender categories.

The combined effect of recognizability and driving style of AVs, along with the appearance of the follower (research questions 3) was tested. AVs driving according to aggressive style tended to result in significantly larger accepted gaps than defensive or mixed AVs. When AVs were not recognizable, or when they were recognizable, but the follower vehicle was an HDV, accepted gaps tended to be smaller than when AVs were recognizable, and the follower vehicle was an AV. The largest accepted gaps were observed when AVs were recognizable, driving according to the aggressive style, and the follower was an AV.

Studying the **effect on the critical gap** (research question 4) revealed that the critical gaps were not significantly different at an aggregate level over all scenarios between the defensive, aggressive, and mixed AV groups. Critical gaps of drivers in aggressive and recognizable AV traffic were significantly larger than those in defensive and mixed recognizable AV traffic when merging in front of a recognizable AV. This was similar to the accepted gaps analysis. When traffic had recognizable AVs, critical gaps of drivers when merging in front of an HDV were not significantly different between defensive, aggressive, and mixed AV traffic. For this condition, it may be noted that the standard deviation of the critical gaps in the aggressive group stood out (1.69) compared to the defensive (1.37) and the mixed group (1.34). A similar observation was made in the accepted gaps analysis. However, when traffic had non-recognizable AVs, critical gaps of drivers were significantly smaller when traffic was composed of aggressive AVs as compared to defensive AVs. This indicates that when traffic has recognizable AVs, their aggressive driving style may induce defensive driving behavior among human drivers as suggested by the increase in their critical gaps. When traffic has non-recognizable AVs, their aggressive driving style may induce aggressive driving among human drivers as suggested by the decrease in their critical gaps. This indicates that aggressive driving style and recognizability of AVs, together affect the critical gap of drivers at *T*-intersections. Gender and age group did not affect drivers' critical gaps.

6.2. Discussion

While Soni et al. (2022) and Trende et al. (2019) found drivers willing to accept shorter gaps in front of AVs, drivers in this experiment accepted larger gaps in front of AVs only when AVs were aggressive and recognizable. When AVs were not recognizable, drivers' critical gaps were smaller when AVs were aggressive compared to defensive. This suggests that the interaction of recognizability and driving style of AVs is important to consider. It is interesting to note that in Soni et al. (2022) and Trende et al. (2019), drivers were provided information to bias their perception of AVs, and in this experiment, driving on the route before the intersections likely affected the perception of AVs. While conclusive comparisons are difficult to draw, a common underlying perceptual mechanism that makes drivers accept larger/smaller gaps when they perceive AVs as relatively unsafe/safe respectively cannot be ruled out. An interesting observation was that aggressive AVs induce more defensive (larger critical gap) driving among human drivers when they are recognizable and induce more aggressive (smaller critical gap) driving when they are not recognizable. Besides comparing the results of this study with previous gap acceptance related research, it is also difficult to reflect on previous studies on car-following behavior as behavioral adaptations in this experiment occurred due to the "carry-over effect" of driving before approaching the intersections. This could also be the reason for the many statistically insignificant findings. Drivers first drove on the route and interacted with traffic, including AVs before they reached and navigated the intersections. Therefore, any behavioral adaptation that could have occurred would be shaped by the drivers' experience before approaching the intersections. It may be expected that there would be more noticeable effects in other behaviors such as car-following or lane-changing where there is more "live" interaction between the drivers and the surrounding traffic. At the same time, statistical insignificance is by itself an important finding that suggests a lack of strong effect of a particular factor. Still, further research that targeted on some of the factors addressed in this research can lead to findings that can yield statistically significant effects.

6.3. Limitations

Along with the results of this study, the study limitations are important to consider. Firstly, the driving behavior of AVs of different driving styles was defined only using a desired car-following time gap parameter. That is, a specifically chosen car-following and lane-changing models were not used. Secondly, the appearance of AVs could have had some effect on their perceived (un)safety. The model and the color of the AVs used in this experiment could have affected the way they were perceived. These were, however, not changed between Defensive and Aggressive AVs. Thirdly, the realism of simulator environments has always been much debated. The control equipment such as the steering wheel and the gas and brake pedals were experienced by participants to be slightly different from their real-world driving experience. Also, the time pressure that drivers felt in the simulator could be different from real-world driving. Still, any potential simulator learning effect was attempted to be compensated by randomizing the scenarios and having a familiarization drive at the start. Additionally, translation of such simulator-environment results into real-world results needs to be done carefully, one of the reasons being the much lower experienced risk in a simulator compared to reality. Finally, although a decent number of participants took part in the study, the sample size may still not have been large enough to satisfactorily check the several considered variables.

6.4. Future research and implications for practice

Future work should study gap acceptance behavior with traffic present on the approach road, both lead and lag gaps. Gap acceptance behavior at left turns where drivers need to consider the traffic from both directions before accepting a gap increases the complexity of the gap acceptance behavior and would be an important direction to explore. In addition, the effect of different penetration levels of AVs in traffic could have implications on the magnitude of human drivers' behavioral adaptation. Given such behavioral adaptation of human drivers around AVs, AV drivers could have different preferences concerning, for example, ACC settings. Decisions of AV drivers in combination with the resulting behavioral adaptations of human drivers are expected to affect traffic efficiency and safety, and therefore important to study. For instance, short (aggressive) headway settings of AVs can be expected to increase traffic efficiency. This must, however, be weighed against the decrease in traffic efficiency caused by defensive maneuvers of other human drivers when AVs are recognizable.

When short (aggressive) headway settings are active for the ACC of recognizable AVs, other human drivers perform maneuvers further away from the AV. This may encourage AV users to keep such short settings as their individual travel experience could become better. This could suggest the exploitation of other (HDV) traffic by AV users. On the contrary, when aggressive AVs were not-recognizable, other human drivers performed more aggressive maneuvers. This could lead to the exploitation of AVs by other human drivers. At the same time, in Soni et al. (2022) and Trende et al. (2019), drivers were observed to perform closer maneuvers around AVs when they are recognizable when drivers have a positive opinion of AVs. This may also be the case when longer (defensive) headway settings are active for the ACC of recognizable AVs. Therefore, other human drivers could exploit AVs also when they are recognizable. Vehicle manufacturers could consider monitoring the attention of AV drivers more frequently, so they are prepared to take over if necessary. External Human-Machine Interfaces could also be a way to control risky cut-ins by other HDVs. One important implication from this study is that if AVs drive aggressively, a behavioral adaptation of other human drivers is most likely to occur both when they are recognizable and not recognizable.

Road authorities are increasingly considering Infrastructure to Vehicle (I2V) communication. Such information could not only include the state of the road downstream, but also explicit instructions for the AV to drive in a certain way. When authorities provide such instructions to AVs in mixed traffic, they need to consider the possible behavioral adaptations. For instance, asking (recognizable) AVs to decrease their headway could cause HDVs to drive in a way that can even decrease traffic efficiency. On the other hand, asking (recognizable) AVs to increase their headway may cause other HDVs to perform risky maneuvers. Examples of V2I situations where this could be relevant are the provision of Variable Speed Limits to AVs upstream, and the provision of time to green information from intelligent intersection controllers to AVs.

CRediT authorship contribution statement

Nagarjun Reddy: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Project administration. **Serge P. Hoogendoorn:** Conceptualization, Writing – review & editing, Supervision. **Haneen Farah:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data will be made available at the end of the project.

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